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Methods of Measuring the Skills Mismatch in the Human Capital Study

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Abstract: The analysis of the labour market in terms of available skills, and especially the skills mismatch, has become increasingly important due to potential problems caused by existing asymmetries. Prior to 2010, when data collection for the Human Capital Study was launched, there were no such analytical tools in use in Poland. On the basis of various solutions, we proposed an innovative approach to measuring both skills and skills mismatches, which since has gained wide recognition. In the article, we present this approach along with its extension to measure specific professional skills in specific industries. We discuss its advantages and disadvantages and compare it with other approaches used in this field.

Keywords: human capital, skills mismatch, skills measurement

INTRODUCTION

The concept of human capital, popularised in economics and other social sciences since the 1960s, initially assumed an ideal vision of the labour market. According to this approach, the increase in human capital resources as measured primarily by the length of education is rewarded in the labour market by means of higher wages (Becker, 1993; Mincer, 1975; Schultz, 1961). However, needless to say that the labour market is far from ideal and is characterised by various asymmetries, and thus the attention of scholars was drawn relatively quickly to skills mismatches (Frank, 1978; Freeman, Richard, 1976; Sattinger, 2012; Spence, 1973). The analyses, carried out since then in many countries, indicate the prevalence of such mismatches, associated with specific effects. Mismatch affects the situation of individuals reducing their wage growth (Chevalier, 2003; Groot & van den Brink, 2000; Mcguinness, 2006), as well as job satisfaction (Badillo-Amador & Vila, 2013; di Pietro & Urwin, 2006). It may also contribute to a reduction in overall physical fitness as a result of not using certain skills that disappear (de Grip et al., 2008) or even a greater risk of depression, which was true for young people unable to find a job due to mismatch (Dooley, 2003). Clearly, mismatch affects the situation of companies not only by reducing their productivity (Mahy et al., 2015; McGuinness & Bennett, 2006; Tsang et al., 1991), but it can also limit innovation (Dupuy & de Grip, 2002; Finegold & Soskice, 1988; Nickell & Nicolitsas, 2000). The effects of mismatch at the level of individuals and companies are cumulative and affect the entire economy and society. It was found that such mismatches are likely to reduce the country's productivity (Haskel & Martin, 1993, 1996) which in turn may hamper its growth. Moreover, there are also additional costs of mismatch reduction incurred by individuals, companies, or public institutions. This is reflected not only in numerous scientific papers dealing with skills (Kocór, 2019) but also in practical activities undertaken by companies (Manpower, 2018), and public policies (CEDEFOP, 2015; European Commission, 2016; OECD, 2019). That is why, it is so important to develop and implement valid and reliable tools for measuring mismatches related to human capital in order to create appropriate recommendations and design appropriate action strategies based on the provided knowledge.

In this article, we present a method of measuring skills mismatch designed as a part of the first edition of the Human Capital Study (HCS)[1], 2010-2015, and further developed in the second edition of the project, 2016-2023. We start by introducing the HCS solutions against the background of other approaches used to measure job-related skills and their mismatches. We discuss the basic assumptions of the HCS and how they necessarily affected the skill measuring procedures and results obtained through them. Topics we cover include measuring universal skills and skills mismatches in cross-sectional studies of the general population and enterprises (HCS), as well as job-specific skills and skills mismatches in specific market sectors in the Sectoral Human Capital Study (SHCS)[2]. We conclude with a discussion of advantages and limitations of the approach used and its possible modifications.

APPROACHES USED TO MEASURE THE LABOUR MARKET MISMATCH

The earliest attempts at estimating the skills mismatch concentrated on the mismatch in the educational dimension, i.e. the differences between the level of education required by employers and that attained by employees. The analysis of the surplus and shortage of education has received the most attention so far (McGuinness et al., 2018), as it is relatively easy to measure this aspect of mismatch by asking for the required and already received education. However, many researchers have been drawing attention to the fairly obvious fact that people with the same level of education do not necessarily have the same level of skills (Allen & van der Velden, 2001; Chevalier, 2003; Green & McIntosh, 2007; Mateos-Romero & Salinas-Jiménez, 2017). As a result, various methods have been developed to estimate the surpluses and shortages of skills. Construction of the appropriate indicators of skill level has proven to be a challenging task, however, and the problem is only exacerbated by differing definitions of the concept. In the last few decades, a number of new methods of measuring skills and skills mismatches were proposed. And while in other countries the phenomenon is well under study, in Poland the skills mismatch as a concept and the associated measuring challenges became the focus of interest only recently.

Prior to the research initiated in 2008 as part of the Human Capital Study project, competency research in Poland only looked at specific skills, such as reading comprehension (literacy) which were a part of the international IALS project of the 1990s (Rynko & Palczynska 2014). HCS was the first research endavour to take into account a broad spectrum of skills as well as information from various labour market participants. A little later, in 2011-2012, a study from the Programme for International Assessment of Adult Competences (PIAAC) series was conducted in Poland, focusing on the measurement of key competences – language, mathematical and computer skills. In 2014-2015, the so-called post-PIAAC collected additional information from respondents participating in the skills measurement. In 2021, another edition of PIAAC research in Poland was started. Based on the data from these studies, it is possible not only to assess the objective level of key skills, but also to calculate mismatch indicators in this area. In 2014 and later still in 2021, Poland participated in the European Skills and Jobs Survey (ESJS), carried out by CEDEFOP, covering some general skills in addition to key competencies. The data obtained were used to determine the areas and extent of skills mismatch in Poland (Chłoń-Domińczak & Żurawski, 2017). Panel data from the POLPAN study on adult Poles (Kiersztyn, 2011, 2013) were also used to analyse the mismatch, though almost exclusively in the educational domain. In each of these projects, a different approach to skills measurement was employed, which resulted in different assessments of the mismatch.

Since the HCS project focuses mainly on the assessment of skills and skills mismatches, when discussing various approaches used in this field, we focus only on methods of assessing skills mismatches, leaving out mismatches in the educational dimension.

One may distinguish two broad types of skill measuring procedures: subjective and objective. The former revolve around variously formulated questions, usually posed to professionally active people, about whether (and possibly to what extent) they make professional use of their skills. For example, respondents may be asked whether they have opportunity to use their knowledge and skills in their current job, or whether they would achieve better results in this job if they had additional knowledge and skills (Allen & van der Velden, 2001). The advantage is that it is relatively easy and quick to collect data on such subjective perception of a potential mismatch, be it a surplus, or deficiency of skills. However, such overgeneralised approach does not allow us to recognise which skills are actually mismatched, and how bad is the mismatch. It is one-sided as it leaves out the demand side of the skills market, namely the enterprises and their skill requirements, which should be the starting point for estimating the mismatch level.

Objective methods partially cope with these limitations by being based not on the subjective opinions of respondents experiencing a potential mismatch but on tests assessing the actual skill level. Thus in the above-mentioned PIAAC studies properly validated tools were used to measure the key competences of literacy, numeracy, and problem solving in technology-rich environments. Based on the results of such objective skills measurement, statistical and mixed mismatch estimation approaches have been developed. The statistical approach determines the average or modal level of competences in any given occupational category and then defines surplus/deficit thresholds in terms of standard deviation. As a rule, mismatched persons are those whose skill level deviates by at least one standard deviation from the average level for their occupation in one direction or the other (Flisi et al., 2017). Simple as it is, this method of estimating mismatch can be criticised for being arbitrary as, similarly to the subjective approach, the level of skill requirements in any given job remains unknown. It also assumes skills to be homogeneous within occupational categories, and the broader these categories are, the more unrealistic this assumption becomes. One can say that the statistical method shows the distribution of skills in a given occupational category rather than the actual skills mismatch.

An attempt to deal with these limitations of the statistical method are mixed approaches that combine subjective and statistical methods (Allen et al., 2013; Desjardins & Rubenson, 2011; Krahn & Lowe, 1998; Pellizzari & Fichen, 2013). Their authors, owing to PIAAC research, propose to use answers to subjective questions about frequency of using certain skills at work or having competences that allow to deal with duties at work to determine matching intervals within which people can be considered fit for work in a given position. For example, in OECD analyses (Pellizzari & Fichen, 2013), an affirmative answer to the question in part F of the PIAAC questionnaire, whether someone has sufficient skills to deal with more demanding duties than those performed in the current job, was considered the upper limit of the matching interval. On the other hand, an affirmative answer to the question that someone needs further training to cope with their current job responsibilities was taken as the lower limit. Then, the distributions of the levels of key competences are prepared for each of the occupational categories in intervals constructed in this way. In the OECD approach, people who are below the fifth percentile or above the 95th percentile are considered mismatches, having a skill deficit or skill surplus, respectively. Attractive as they are, mixed approaches are again subject to criticism for not being derived from actual skill requirements but being rooted in the subjective perceptions of respondents.

Another limitation of all objective approach methods is that they can only measure key skills like language, math or computer skills. However, they do not say anything about general skills (sometimes called transferable or specific professional skills (necessary to work in a given position or profession). Obviously, this is related to the difficulty of measuring such general and professional skills. The PIAAC study, which is used in the objective approach, is based on well-validated tests of key skills, because these are, on the one hand, relatively easy to compose and, on the other, such skills can be estimated for the entire population. Designing objective tests for general or professional skills proves to be very complex and difficult.

SKILLS MEASUREMENT IN THE CROSS-SECTIONAL HUMAN CAPITAL STUDY

From the very beginning, the basic premise of the HCS approach was to combine insights from both sides of the labour market: employers who set the skill levels required for particular job positions, and employees or job-seekers who provide varying levels of particular skills[3]. This has been achieved by making it possible to compare employees' self-evaluations with employers' requirements regarding a set of general skills. Various forms of skill questions, used in diverse national and international research projects, were consulted before arriving at the final formulation of the relevant part of HCS questionnaire.

In the HCS, competences are conceptualised as knowledge, skills, capabilities, attitudes and other human traits needed to perform specific activities (professional tasks), regardless of the way they have been acquired (Strzebońska & Dobrzyńska, 2011). Competences were to be measured by means of respondents' self-assessment using five-point scales. In the first edition of the study, 2010-2014, a total of 12 main competences were distinguished, some of which were further broken down into sets of partial competences, increasing the number of all analysed competences to 34 (Czarnik & Kocór, 2015; Kocór et al., 2020)[4].

In the introduction to the relevant part of the questionnaire, self-assessments were placed in a strictly professional context by telling respondents to think of them as possibly job-related. Additionally, in the first three years of the study (2010-2012), respondents were asked to distinguish between self-assessment of actual skills and the willingness to perform work that requires those skills. This aimed to distinguish competences "active in the market" from those that the respondents did not intend to use professionally. It was also meant to elicit more accurate responses by prompting the respondents to reveal their current level of skills, rather than the level of skills to which they aspire due to preferred type of work. The relevant part of the questionnaire was preceded by the following introduction:

> *Different types of work require different skills and abilities. It is often the case that in one or two areas our capabilities are relatively high, while in others they are much lower.*
>
> *Everyone also has a certain idea of a work they would like to do. Sometimes we can do something very well but would not like to do it as a part of our job. On the other hand, we may very much want to have a certain kind of job but not have the necessary skills yet.*
>
> *Now I am going to read to you a list of various skills. For each of them, I will ask you to assess your own skill's level on a 5-point scale, where 1 stands for "low", 2 for "basic", 3 for "medium", 4 for "high", and 5 for "very high".*

Then I will ask if you would like to do work requiring that skill, again using a 5-point scale, where 1 stands for "definitely not", 2 for "rather not", 3 for "neither yes, nor no", 4 for "probably so", and 5 for "definitely so".

In point of fact, skills self-assessments turned out to be very strongly correlated with willingness indicators as evidenced by high values of Pearson's r coefficient. Half of the correlations were greater than 0.8, and of the remaining ones, almost all exceeded 0.7. The only exception was "stress resistance," for which the correlation was 0.688. It may also be of note that the correlation for "making simple calculations" was barely higher at 0.709. It should be emphasised that such strong correlations occurred not only at the level of general sample but also within particular occupational categories. Therefore, in subsequent editions of the study, inquiry was limited to skills self-assessment only (Czarnik et al., 2011).

In the case of self-assessments, the question of measurement validity is particularly relevant. Social desirability bias, i.e. the respondents' tendency to positive self-presentation, may lead to overestimation of one's skills and, as a result, to spurious homogeneity of (high) assessments (King & Bruner, 2000; Oppenheim, 2004). In reality, mean self-assessments on 1-through-5 scales ranged from 2.0 (knowledge of specialised computer programs) to 3.8 (contacts with other people), while standard deviations were between 0.90 and 1.45 (Czarnik et al., 2011). Mean comparisons between sub-major occupational groups of the second tier of International Standard Classification of Occupations (ISCO-08) provided some evidence for criterion validity of self-assessments: for all but two skills, the differences between the best and the worst performing professional groups exceeded one point; for some skills (mathematical, managerial, office, technical) they approached two points, while for computer skills they were as high as three points. In the case of computer, office and cognitive skills, the eta^2 coefficient exceeded 0.2, meaning over 20% of the self-assessments' variance could be attributed to the type of occupation as defined by the second tier of ISCO-08. Particular professional groups had predictable advantages in terms of specific skills. Managers had the highest self-assessment not only of managerial skills, but of self-organising, cognitive and office skills as well; information and communications technology professionals excelled at computer skills; both clerks and business/administration associate professionals topped the ranking of office competences; mechanics, assemblers, and electricians had the highest self-assessment of technical skills. All main skills (except technical ones) were strongly related to the level of education completed. Additionally, within each major occupational group (the first tier of ISCO-08), higher self-assessment of any particular general skill in a statistically significant manner translated into higher earnings while controlling for age and gender. The above results, promising as they were, still left a substantial space for disputes over the validity of self-assessments HCS style.

In the second edition of the HCS project (2017-2023), the list of skills tested was slightly modified. An attempt was also made at assessing the validity of selected skills self-evaluations by adding short skill tests a the end of a questionnaire. To test the validity of computer skills self-assessments a simple IT quiz was added in 2017 survey. Due to the time restraints of the interviews, quiz was limited to the knowledge of basic computer terminology. The test outcomes turned out to correlate with the self-assessment of computer/tablet/smartphone usage skills (r=0.563), as well as the specialised computer programmes' usage skills (r=0.583) (Koniewski et al., 2019). In the HCS 2021 edition, a short mathematical test was appended. Initial analyses show that the test outcomes correlate with self-assessments of mathematical skills (such as ability to perform simple or advanced calculations), although these correlations are substantially lower than those observed for computer skills previously. This is largely due to the fact that consent to participate in the test was clearly negatively correlated with the level of self-assessment of mathematical skills which in itself may be indicative of self-assessment's validity. It is also worth adding that specific skills selected as first to be tested for validity of self-assessments were both relatively easy to be faithfully self-assessed and to be objectively measured by means of a short quiz. The challenge for the future editions of the HCS will be the objective measurement and testing for the validity of soft skills self-assessment.

SKILLS BALANCE

Owing to the standardised approach to skills in all modules of the HCS project, it was possible to directly compare the self-assessments of skills characterising job seekers in specific occupational categories with the skill requirements set by employers recruiting employees in these occupational categories (Czarnik & Kocór, 2015). Just as respondents in the population study were self-assessing their competences on 5-point scales as low, basic, medium, high or very high, employers were to use such same 5-point-scales to indicate levels of skills (defined in identical terms) required of candidates for specific job positions[5].

To compare the self-assessment of skills with the skill requirements, both the self-assessments and the requirements were subjected to double relativisation (centering). When assessing the level of self-assessment or the requirement for a specific skill in a specific occupational category, it was taken into account both how important this skill is in relation to all skills in this occupation, and how important this skill is in this particular occupation in comparison to all occupations.

The double relativisation of self-assessment is given by the formula:

$$\boldsymbol{S_{cj}} = \bar{s}_{cj} - \bar{s}_j - \bar{s}_c + \bar{s}$$

where:

$\boldsymbol{S_{cj}}$ denotes (double) centred self-assessment level of a competence $\boldsymbol{c}$ in a job $\boldsymbol{j}$;
$\bar{s}_{cj}$ denotes the average self-assessment of a given competence c in a given job j;
$\bar{s}_j$ denotes the average self-assessment of all competences in a given job j;
$\bar{s}_c$ denotes the average self-assessment of a given competence c in all jobs;
$\bar{s}$ denotes the average self-assessment of all competences in all jobs.

Similarly, the relativisation of skill demands was carried out according to the formula:

$$\boldsymbol{D_{cj}} = \bar{d}_{cj} - \bar{d}_j - \bar{d}_c + \bar{d}$$

As a result of this double relativisation, the skill self-assessments and demands are freed from the differentiation due to certain skills generally scoring higher/lower than other skills, as well as certain occupational categories scoring generally higher/lower than other occupational categories. Thus, the average level of self-assessments and demands for any one individual skill, as well as the average level of self-assessments and demands in any one professional category, are brought to zero. In the effect, the balance based on $\boldsymbol{S_{cj}} - \boldsymbol{D_{cj}}$ differences takes into account both how a given professional group self-assesses its level of a given competence as compared to other competences and other groups, as well as how much of this competence employers demand from this professional group as compared to other competences and other professional groups.

Such an approach may be used to indicate potential areas of skill mismatch. Comparing employers' demand for particular levels of skills with the supply of skills in the labour market by current employees, the unemployed or students just entering the market is a unique feature of the HCS survey. Presented below is Table 1 showing an example of the balance for major occupational groups (first tier of ISCO-08) as regards the unemployed job-seekers.

Table 1. Skills balance as difference between self-assessment and requirement (data doble-centred relative to occupational categories and competences).

	PER	SLF	AVL	LAN	PHY	COG	COM	MAT	TEC	MNG	OFF	ART	Total
PROF	-0,25	-0,13	-0,16	-0,12	0,55	-0,27	-0,31	0,17	0,03	0,26	0,20	0,03	0,00
ASSO	-0,22	-0,14	-0,04	-0,06	0,48	-0,32	-0,28	-0,15	0,28	0,33	-0,19	0,29	0,00
CLER	-0,29	-0,06	0,21	-0,14	0,50	0,05	-0,36	-0,13	-0,07	0,32	-0,40	0,39	0,00
SERV	-0,26	0,05	-0,07	-0,11	-0,05	0,16	0,19	0,04	0,11	-0,03	0,15	-0,18	0,00
CRAF	0,32	0,07	0,11	0,29	-0,52	0,15	0,26	-0,05	-0,15	-0,31	0,04	-0,19	0,00
OPER	0,06	0,10	-0,35	0,15	-0,52	0,26	0,47	-0,01	-0,22	0,01	-0,01	0,05	0,00
ELEM	0,21	0,02	-0,17	0,24	-0,80	0,15	0,48	0,11	0,02	-0,19	0,00	-0,06	0,00
Total	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00

Skills: ART – artistic, OFF – office, AVL – availability, PHY – physical, PER – interpersonal (contacts with other people), LAN – languages, MNG – managerial, COG – cognitive, COM – computer, MAT – mathematical, SLF – self-organisational, TEC – technical.

Occupations: PROF – Professionals, ASSO – Technicians and Associate Professionals, CLER – Clerical Support Workers, SER – Services and Sales Workers, CRAF – Craft and Related Trades Workers, OPER – Plant and Machine Operators and Assemblers, ELEM – Elementary Occupations.

Source: HCS – Population Study 2010-2013, Employer Study 2010-2013.

An example of such a balance for the 2010-2013, data shows a clear division between white-collar and blue-collar occupations in the arrangement of two general skills: physical fitness and computer skills. This is due to the rather obvious specificity of such jobs: in white-collar occupations physical fitness is less needed than other skills, and it is also relatively less needed than in other occupations, hence surplus. The contrary is true for computer skills, which are relatively more important as compared to other competences and more useful than in other occupations, hence shortage. A reverse pattern may be observed in the blue-collar occupations.

BEGINNINGS OF THE SECTORAL HUMAN CAPITAL STUDY

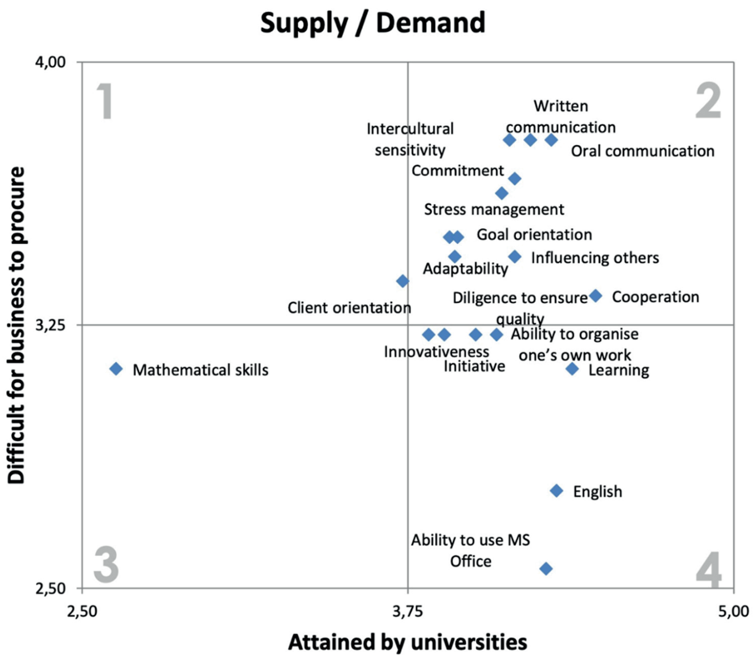
The characteristic feature as well as a limitation of the HCS was that it included only general competences while leaving out any job-specific skills. As a result, these studies did not allow to provide an answer to the question about the professional skills mismatch existing in specific sectors of the economy. Finding an answer to this question was important from the point of view of influencing the process of education and apprenticeship at various levels of the education system. The first approach to solving this problem, initiated in Cracow, was to develop a balance of skills and requirements for the BPO and ITO (2012), energy, passive and energy-saving construction, life science and creative industries (2013), construction, architecture and IT industries (2014), as well as tourism industry, transport and logistics, and foreign languages (2015). Research methodology, which was referred to as "Cracow balance sheets,"[6] was based on a combination of secondary data analysis, qualitative and quantitative methods, and the study of two types of entities significant for the labour market: human resources managers of the largest companies in each industry as well as directors of educational units educating graduates for work in particular business sectors. Recruitment ads, competency dictionaries and other documents provided by companies as well as school and university curricula were also subject to analysis.

Two questionnaires were used as primary tools for analysing the balance of skills within the Cracow balance sheets study. The "demand sheet," filled in by representatives of human resource departments of companies, contained data on current and anticipated skills requirements. Human resource directors were asked to provide information on: a) names of jobs for which recruitment was conducted among university graduates; b) the anticipated number of new employees who will be employed in the above-mentioned positions; c) requirements as to the type and level of skills of candidates for the above-mentioned positions; d) the importance of each skill for the company and difficulties in obtaining them.

The "supply sheet," filled in by universities representatives, collected information on the learning outcomes currently achieved and the forecasts of the number of graduates in fields related to the industry. The surveyed representatives of universities were asked to: a) indicate the names of fields of study, profiles and specialisations conducted within the field of study in line with the industry profile; b) specify the anticipated number of graduates who will complete the specialties in the next five years; c) indicate the extent to which individual learning outcomes are achieved in each of the given specialisations (on a five-point scale).

Based on the data obtained, a mismatch matrix was created, consisting of two dimensions: the difficulty of acquiring skills from the perspective of employers, as well as the achievement of the intended learning outcomes as assessed by education representatives. Using both dimensions, it was possible to identify four areas, represented by four fields in the mismatch matrix. Figure 1 provides an example of the matrix from the 2012 study, including skill levels obtained at the university majors/specialisations relevant for the ITO/IT industry and employers' perceived difficulty in recruiting people with such skills.

Figure 1. An example of a demand/supply matrix from the study “Bilans kompetencji branż BPO i ITO w Krakowie” (2012).



Source: own elaboration.

The sectoral study of human capital for Cracow was continued until 2015 and, apart from creating a platform for discussion within the ‘business-university-local government’ triangle and offering specific solutions to cope with the skill mismatch between universities and specific industries, it was an inspiration for the creation of nationwide, industry-specific methodologies for skills studies.

MEASUREMENT OF MISMATCH IN SECTORAL RESEARCH

To determine the demand for professional skills and mismatches related to these skills, in the second edition of the HCS, 2016-2023, mismatch measurement has been carried out in two ways. As a part of the cross-sectional study, the mismatch in terms of general skills is still estimated based on the same model. The changes concerned only the extension of the list of skills, which has already been mentioned. At the same time, sectoral research under the name of the Sectoral Human Capital Study (SHCS) is also conducted, with the focus on the analysis of mismatches in professional skills related to job positions which are of key importance for a given industry. The research has been carried out so far in several sectors in which there are Sector Skills Councils, including the sectors of construction, marketing communication, modern business services, finance, trade, IT, tourism, fashion and innovative textiles, development services, healthcare and social assistance, as well as aerospace industry. The approach to examining professional skills was based on the model developed in the Cracow balance sheet study; however, several fundamental modifications were made to it. The most important of these is estimating the mismatch for each position and not for the sector in general, and taking into account all key positions in the analyses, not only entry-level positions (which are offered to graduates and do not require experience).

The SHCS approach is a multi-stage solution using both methodological triangulation and data source triangulation. In the first step, key business processes for each industry are determined through the analysis of secondary data and qualitative research (in-depth interviews with experts). For these processes, in subsequent stages of qualitative research, the key positions necessary to implement these processes are identified. Then, again on the basis of existing sources and expert interviews, skills' profiles are constructed. It is worth mentioning that, whenever available, the Sectorial Competency Framework informs the process of skill profile definition. These profiles are subdivided into separate categories of knowledge, skills and social competences, a categorization typically used in the domain of public policies. Such skills' profiles for key positions related to the main business processes are verified during expert panels. They constitute a starting point for quantitative research carried out on random samples of companies from the industry. Within a company, a convenience (non-probability) sample is selected of persons performing the tasks of a key position.

In SHCS, three types of asymmetry in the skills dimension are included: mismatch, skills gap and a forecast of changes in this area in the future. The mismatch is estimated by comparing employers' declarations on the importance of skills included in the skills' profiles for key positions and the assessment of the skill level possessed by employees in such key positions. Comparing the responses allows measuring the mismatch at the level of key positions by distinguishing four basic categories of skills: balanced skills – relatively more important for employers and, at the same time, relatively highly rated by employees; surplus skills – relatively less important for employers but with higher employee self-assessment; shortage skills – relatively more important for employers with lower self-assessment of employees; sufficient skills – relatively less important for employers with, at the same time, poor self-assessment of employees.

It should be emphasised, however, that a skills mismatch thus estimated is of relative nature, as any given skill self-assessment/requirement is expressed relative to other skills, rather than being expressed in absolute terms. The procedure entails the computation of average levels of requirements and self-assessments for all skills in the profile of a given position taken together, and then the average requirement and average self-assessment for each particular skill are compared to the respective averages for the entire skill profile. Therefore, a given skill is labelled as "relatively more," or "relatively less important" if it scores higher or lower than the average for all skills pertinent to the position. This relativisation procedure aims to make the results more realistic and to avoid possible errors in conclusions, which may stem from direct comparisons of the assessment of the importance of competence necessary in a given position and the self-assessment of skills held by employees. This relativisation procedure has both supporters and critics. An alternative solution may involve centering – using as a benchmark the mean of all skill assessments for all key industry positions, which would allow to analyse each skill of a given position against skills in the industry as a whole. Ultimately, the choice of one of these approaches depends on specific research objectives.

The SHCS research also identifies skill gaps, which is of great importance especially for employers and the educational institutions, as it allows to check whether there is a shortage of people with skills that are significant to employers, and to take specific actions. In industry research, the skill gap is treated as a situation in which employers indicate the existence of skills, perceived by them as relatively important and, at the same time, difficult to obtain in the labour market.

The assessment of the mismatch in terms of skills in the SHCS research is supplemented by the forecast concerning the demand for each competence in the next few years. Depending on the specifics of the industry, the market situation or other factors (such as the COVID-19 pandemic), employers are cautious about long-term predictions and questions about them concern a shorter perspective – a year or the next 2-3 years, and less often 3-5 years. Therefore, the study is supplemented by the use of foresight methodology in industry research, serving to create forecasts based on the expert knowledge of sector representatives, scientists, and decision makers. In the SHCS study, the Delphi method (a forecasting approach based on a survey of selected experts) as well as expert panels have been used.

CONCLUSION

Negative consequences of the skills mismatch necessitate accurate estimation of the type and size of the mismatch. Until recently, research on these issues was largely limited to the educational mismatch (Kocór, 2019; Mcguinness, 2006). In recent years, however, more emphasis was placed on skill-related asymmetries (Flisi et al., 2017). Conducting such research is challenging due to the complexity and variation in skill definitions, and proves especially difficult as far as objective measurement is required. Moreover, for those active in the labour market, education and public policies, the mere measurement of key or general skills is hardly sufficient. In effect, in many countries the so-called Skills Councils are being developed to analyse the mismatch in specialist professional skills. The complexity of this procedure is illustrated by the example of the Sectoral Human Capital Study.

The approach to measuring skills adopted and developed in the HCS and SHCS studies has already been appreciated, both in Poland (Lewczuk, 2018; Ministerstwo Edukacji Narodowej (Ministry of National Education), 2019; Ministerstwo Rozwoju (Ministry of Economic Development), 2020) and abroad (European Commission, 2016; OECD, 2019). The advantage of this approach is that it combines data on supply and demand for skills in the labour market. While in alternative approaches skill requirements for particular job positions, which constitute the demand-side in the skill market, are contextual or arbitrarily set, in the HCS they are explicitly included. The method allows for much flexibility in measuring skills, including key, general and professional competences. The lists of skills and skill profiles can easily be updated and modified. Yet another advantage of this approach is that it involves industry experts, both in the process of identifying key positions and in developing skills' profiles for these positions. Thus, the research process takes into account the changes that occur in sectors under study and it involves experts-practitioners in its implementation and critical decisions.

To be sure, the research approach developed in the HCS and SHCS studies has its limitations. Disadvantages include difficulties in obtaining accurate information from representatives of various sides and sectors of the labour market. For one thing, decreasing response rates in surveys based on random samples are a growing concern. A separate issue is the declarative and subjective nature of the data collected on the levels of skills possessed by and required of employees and job-seekers. This problem requires careful attention, even if one is forced to admit that objective measurement is hardly an option in any wide-scope general-population survey, covering various market sectors and people in diverse professional roles. In the second edition of the HCS, steps were taken to test validity of selected skill self-assessments, which yielded satisfactory results for ICT and mathematical skills. Still, there is surely room for improvement. A reliable estimation of the skills mismatch at the level of the entire economy and individual sectors of the labour market remains a challenge for researchers and analysts.

NOTES

1 In Polish, the project is known by the name of Bilans Kapitału Ludzkiego (BKL).
2 In Polish, the project is known by the name of Branżowy Bilans Kapitału Ludzkiego (BBKL).
3 Additional data were collected form high schools and universities to include young people yet to enter the labour market.
4 Since 2012, "fluent use of the Polish language" was considered a principal competence while "Internet usage" and "delegating task to other employees" were abandoned.
5 With the exception of the lowest item on the scale, which in the employers' survey defined competence as "not necessary", all other labels describing the required level of competence were the same as the respective self-assessment labels in the population survey.
6 In Polish, "bilanse ośrodka krakowskiego".

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